Concept of a Method for Change Detection in Topobathymetric Point Clouds

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Abstract: Change detection of 3D point clouds is addressed in multiple research projects. This paper introduces a concept for change detection in topobathymetric point clouds based on topobathymetric full waveform laser scanner data. Airborne laser data with a green laser not only includes hard targets or volumes, given e.g. by vegetation, but also points from the water surface, underwater inhomogeneity and river ground. Challenge of the intended work is to detect changes in waterbeds, in the water level or calculate the morphodynamic of rivers. The change detection in topobathymetric point clouds requires pre-processing like the co-registration of multi temporal point clouds, segmentation and classification. A concept for the processing chain is proposed. First results of the segmentation by region growing are shown of the test site of the river Mangfall in Bavaria, Germany.

1 Introduction

Bathymetry is the measuring of underwater depth of seas, oceans or other large bodies of water. In general acoustic and optical sensors can be used in which latter can be distinguished into active and passive techniques. A passive way to determine the water depth is by colour bathymetry. The water depth calculation depends on the water colour in an image (DELAI et al. 2014). An active case of bathymetry is the airborne laser bathymetry (ALB). For that, a green laser mounted on an airplane, is used to measure points under the water surface. This was first used to detect submarines from the air in the 1960's. Additionally to the green laser, infrared lasers are used in combination (PFENNIGBAUER et al. 2010; STEINBACHER et al. 2012). While the infrared laser reflects on the water surface and measures the surface, the green laser penetrates the water and measures the water ground. To ensure the water penetration, the laser beam have an incidence angle of approximately 20 degrees to the water surface. Measuring morphodynamic changes after flood events and evaluating the impact of this changes on instream habitats based on topobathymetric point clouds from a combined infrared and green laser (MANDLBURGER et al. 2015). This kind of river monitoring is needed to satisfy the aims of the European Directive 2000/60/EC (EUROPEAN UNION 2000) and create flood risk maps, required by the European Directive 2007/60/EC (EUROPEAN UNION 2007).

A topobathymetric point cloud is a set of points mapping the water surface, the river ground and the river waterfront. Changes of water levels and the river beds can be captured by point clouds taken from sub sequent flights. The search for new or missing points is the task of the change detection. New points can be produced by new buildings or deposits on the ground or waterbed. Also a growing tree produces new points in another scan time. In contrast to that, the drift of water ground points, landslides, demolished buildings or fallen trees are determined by missing points

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in the second scan time. So it can be used to recognise movements in the river ground points or to determine and control the water level. The challenge from such a change detection is, that the discrete position measuring of the laser scanner typically differ between two times. Furthermore, occlusions have to be considered and change detection of vegetation is a challenging task due to the volumetric reflections and changing canopy properties. Therefore, an accurate co-registration of the two point clouds to the two time stamps is needed for the change detection.

The co-registration of point clouds has the aim to create transformation parameters from one point cloud to the other. With this transformation it is possible to adjust the offset and orientation misalignments between the point clouds, caused by the measuring inaccuracy. The adjusted transformation parameters are further used to assign one point in the first point cloud to the corresponding point in the other point cloud. For the registration it is important to know which class the points belong to. By knowing the class of potential matches, mismatches, like ground to building points, are avoided. Furthermore, the class information can be used for the change detection by defining probabilities of changes. For example, vegetation points change with a higher probability as ground points.

Chapter 2 show related works in the fields of full waveform analysis, point cloud classification, registration and change detection. The proposed concept and its processing chain is shown in chapter 3. An overview of the used test site is given in chapter 4 and the last chapter shows the first results.

2 Related work

2.1 Full Waveform

Laser scanners rare divided into the ones, which recognises only the time stamps to each returning impulse and the ones which recognises the whole returning signal. This so-called full waveform must be analysed to derive discrete points. JUTZI & STILLA (2006) show how to separate the full waveform signal into multiple returning pulses along the laser beam. For this, the sent waveform is used to find reflections of scatters. Additional attributes, like the number of returns are derived from the entire signal and assigned to each point. This information can be used to determine multiple classes, including single, first, last and middle pulses (REITBERGER et al. 2008). Furthermore, the returning signal can be used for a vegetation classification (RUTZINGER et al. 2008) or to segment tree crowns and tree stems (REITBERGER et al. 2009).

2.2 Classification

The point cloud classification can be divide into two main parts. The first part is the segmentation and the second one the matching of class labels to the segmented regions. The segmentation aims for the creation of regions of connected points. Most of these segmentation approaches are point based (RUTZINGER et al. 2008; SHAPOVALOV et al. 2010; ZHANG et al. 2016). For that, k nearest neighbours are searched and connected to a graph. To build the segments from this graph, there are methods for a region growing, which combine points, for example on the base of their echo width (RUTZINGER et al. 2008). Or a graph cut at the local maxima of the points height values is used (ZHANG et al. 2016). Another base for such segmentation are volume clusters, so called voxels. These voxels have a defined neighbourhood and are segmented together, if they are close in position and their intensity or colour difference is below a threshold (AIJAZI et al. 2013). To match a segment to a specific class, a descriptor has to be calculated. These descriptors are used to define the properties of a specific class. In the case of voxels, the descriptor can consist of the surface normal or the geometry of the segment. Other additional descriptor attributes are the height differences between the geometrical centre and the barycentre. For non-geometric attributes, intensity or colour values can be chosen (AIJAZI et al. 2013). In the point wise classification, machine learning approaches were used. ZHANG et al. (2016) uses trained SCLDA-based features as their descriptors. Furthermore, they apply an AdaBoost classifier to match the features to a class. Another machine learning approach is to use Markov random fields, like in SHAPOVLAV et al. (2010). For this Markov random field, they need a unary potential, which is the descriptor for each single point and a pairwise potential, which is the descriptor for an edge in the graph. For the unary potential spectral and directional features, spin images, angular spin images and distributions of heights are used. The angle between normals, the difference in altitudes and the difference in positions are their pairwise potential. NIEMEYER et al. (2014) uses conditional random fields instead of Markov random fields. They use linear models and the Random Forest algorithm to train and obtain their unary and pairwise potentials. These potentials are calculated on the base of intensity, echo numbers, height above a digital terrain model (DTM), point densities and some other feature attributes. RUTZINGER et al. (2008) uses a classification tree based on the echo width, echo ratio and dense ratio of the segments. But they have only the aim to detect vegetation points, so the classification tree isn't very deep. A detailed segmentation and tree species classification is shown in REITBERGER et al. (2008) and a segmentation based on graph cuts in REITBERGER et al. (2009).

2.3 Registration

The extraction of transformation parameters from one point cloud to another, is the aim of the registration task. Existing approaches are summarized in a review by SALVI et al. (2006) and TAM et al. (2013). The registration methods can be divided into coarse and fine registration (SALVI et al. 2006). A simple method to register surfaces are point signatures, which are calculated from the intersection of a sphere, centred at point P, to the local surface of P of each point (CHUA & JARVIS 1997). Another way is to use a principal component analysis (PCA) based approach, which looks for corresponding principal axis of the covariance matrix of neighbouring points (CHUNG et al. 1997). JOHNSON (1997) introduces spin images, which accumulate each point of a surface into a tangent plane to a specific surface point. Therefore, the distance from the normal vector of the specific surface point to the other surface points and the distance from these surface points to the tangent plane, are used as the axis of the spin image. TAREL et al. (1998) uses a polynomial representation of a surface function to model surfaces and matches these functions. BRUNNSTRÖM & STODDARD (1996) have shown, how to build a genetic algorithm for the registration task. This chooses points on the surface randomly and defines the best match by a fitness function. This fitness function depends on angles between normal vectors and the distance between two points.
The most common fine registration algorithm is the iterative closest point (ICP) algorithm (BESL & MCKAY 1992). This algorithm starts with a seed estimation of the transformation parameters. After this initial transformation the algorithm searches for the best transformation parameters by minimizing the distances between the point correspondences iteratively. Another method to model

surfaces is to use signed distance fields (MASUDA 2001). The distance from a point to the surface and the surface normal approximates a so called signed distance field (SDF) of the surface to the closest point. Two surfaces are matched together by minimizing the distance between two SDFs. With the focus on the surface type, the registration methods can be divide into rigid and non-rigid (TAM et al. 2013). In the special case of airborne laser scanning data, a rigid PCA based approach creates good results (HEBEL & STILLA 2009; HEBEL & STILLA 2012). Here, roofs were used as rigid surfaces and enables also a calibration of the airborne laser scanning (ALS) system.

2.4 Change Detection

A change detection can be implemented either point based or voxel based. The idea for the point wise change detection is to subtract meshes. This can be for example a digital surface model (DSM) (MURAKAMI et al. 1999). Here, the difference between the elevation of two DSMs is projected to a change image. This is used to detect building changes in ALS data. Another approach which subtract digital elevation modesl (DEMs) is shown by MANDLBURGER et al. (2015). To differentiate true changes from measuring noise, a statistical test is used to detect significantly changes. This is used to model the morphodynamic of a river. A voxel structure and laser beam reconstruction can be used for change detection as well (HEBEL et al. 2013). New points are detected, if the laser beam traverses occupied voxels in the reference data. If the laser beam comes to lie in an empty voxel in the reference data, the traversed voxels of the beam are marked as free areas. Another method is to compare distances and plane intersection angles between two voxels of two point clouds (GIRADEAU-MONTAUT et al. 2015). This detects not only changed points, it also calculates how far the points have moved. A Hausdorff distance performs best results in this context. The Hausdorff distance is the distance from one point to its closest point. To get this GIRADEAU-MONTAUT et al. (2015) calculate the distance from one point to all others in neighbouring voxels and search for the shortest distance.

3 Concept

This paper proposes a concept for a change detection. This consist mainly of three parts. The first part is a classification of the point cloud data. In the second part two point clouds from different times will be registered, using the results of the classification. And the third part is the change detection itself, using the results from the classification. All three parts are implement on the base of a voxel structure. Since the data is very big (up to 200 Mio points) it is not suitable to build a graph, based on all points. Instead of this, a voxel space is used as a generalisation of the point cloud. The concept scheme is shown in Fig. 1.

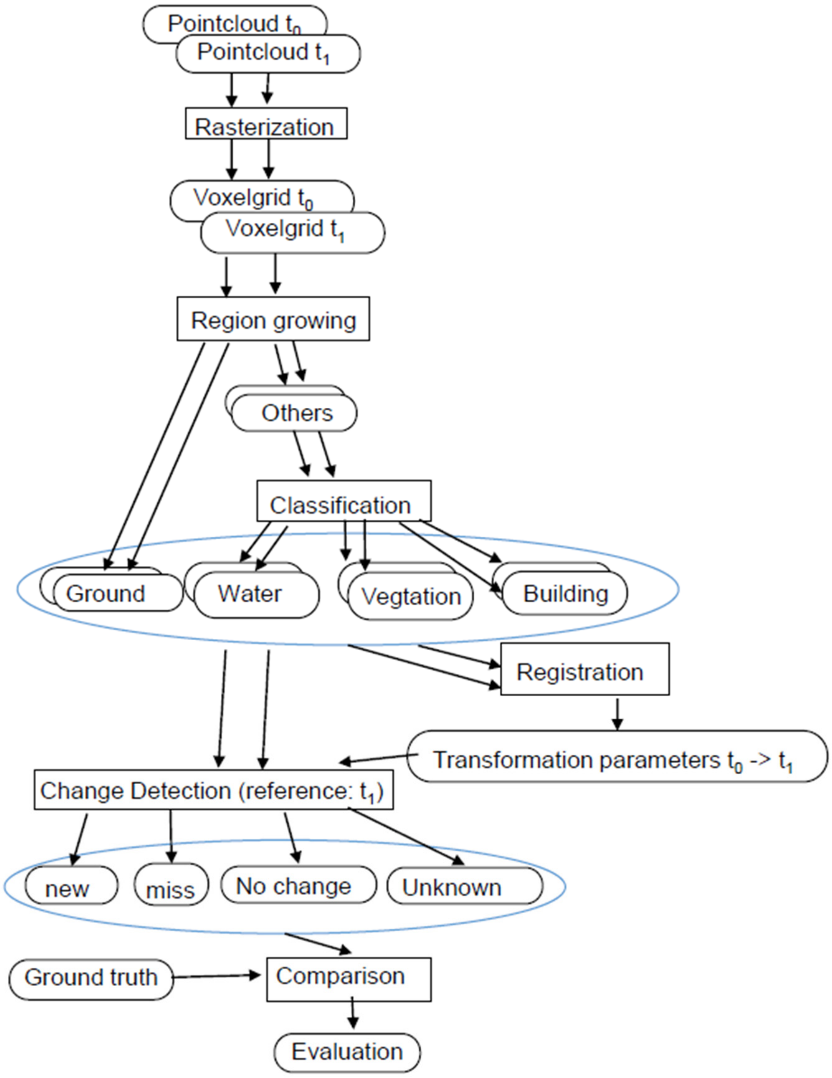

Fig. 1: The proposed concept. The rectangles show the processing steps which create the output in the ellipses. These outputs are used for further processing, which is shown by the arrays. These arrays point from one output to the processing step which needs these output.

The classification segments the point cloud into ground, water, vegetation and building points. This labels are further used in the registration to avoid mismatches, for example from ground points to building points. Furthermore, a change in vegetation points is much more probable as a change in ground points. So the class labels must also be used in the change detection part. To classify the point cloud, the cloud has to be segmented first. For this segmentation, neighbouring voxels can put together on the base of attributes, like the intensity difference (AIJAZI et al. 2013). In this way a region growing algorithm on the base of voxels creates segments of points with same conditions. The voxel classification presented in AIJAZI et al. (2013) uses a linear match of the calculated descriptor to the class labels. The proposed method will use a machine learning algorithm for this task. The advantage of the machine learning algorithm is, that they can be easily adjusted to new classes. So the classification method can be adjusted to another classification application in the future. Possible machine learning algorithm for a match of a single descriptor to a class label are Random Forest or support vector machines.

The registration of natural scenes is a challenging task as plane structures which are easy to co register mainly appear only in urban areas. In the case of voxel structures the concept introduces a combined coarse and fine registration. The coarse registration uses bigger voxels, so that they don't change between two times (if the landscape doesn't change drastically). An iterative algorithm, which uses iteratively smaller voxels, solves the fine registration. In addition to the geometrical shape of the voxel structure, the class information of each segment, and therefore the voxel, is used to roughly filter match-able and not match-able voxels. Therefore, only voxels of the same class are considered in the pairwise matching process. Furthermore, a hybrid data structure is used to model ground points as a DTM and register two DTMs. Volumetric parts like water and vegetation, are modelled as a voxel structure and handled in a different way for the change detection.

The change detection, proposed by HEBEL et al. (2013) is suitable for voxel structures and detects missing points as well as new points. But changes inside one voxel are not detected, so there has to be some fine adjustments. Dependent on the voxel size the ground points can change in a sub voxel manner. Therefore, a conversion from the voxel space to the point space is needed in the change detection, like in GIRADEAU-MONTAUT et al. (2015). But the calculation of distances from one point to all other inside a voxel is very computational expensive. To fuse the voxel and point wise change detection approaches, there is a first change detection on voxel base. This is done by a ray tracing of the laser Beam (HEBEL et al. 2013) or by defining attributes, which are checked for a change. A significant change in density for example can mark therefore changed voxels. These changed voxels are further compared with a point wise change detection. The implementation of the point wise change detection is dependent on the point type. Therefore, solid points can be compared with another method as water or vegetation points. The calculation of differences in DEMs performs a suitable change detection for solid points. So if the changed voxel consists of solid points, the next step is to calculate the difference of the DEMs for this points. For water points, the point wise change can be calculated with the distance of two fitted planes to the water surface. Vegetation points can further be checked of the whole bounding box difference. So that the point wise change detection calculates volume changes. Thresholds, defining a significant change, depend on two parameters. One parameter for each class, so that the threshold for vegetation points is in general higher, than for others. The second parameter for the threshold is a global one, which considers measurement accuracy and misalignments from the registration before.

4 Experiments

First algorithmic tests of the proposed method are performed on a dataset of the Mangfall area in Bavaria, Germany (Fig. 2), recorded with a VQ 820G Scanner. The dataset reaches from the Tegernsee to the highway A8. The whole scan for the first flight consist of nearly 200 Mio points and maps a flight strip of nearly 17 km length and 500 m width. On the ground, the point distance in a single flight strip is 4 dm. A water penetration up to 5 m was reached with the laser beam. The laser scanner measures with a wavelength of about 532 nm. By a flight height of 500m, the laser beam gets a 50 cm footprint. Furthermore, the scanner is able to create a high spatial resolution of 20 to 50 points/m². A rotating multi facet mirror, used as the scan mechanism, ensures an incidence angle of 20° with respect to the flight direction, with an accuracy up to 1° (STEINBACHER et al. 2012). The scanning system uses a full waveform approach, which recognises up to 4 pulses inside a single laser beam. Recognised point attributes are the intensity, the number of returns, the return number, the scan angle rank, the GPS time and two flags which determine the scan direction and flight line edge points.

Fig. 2: The scanned region (Photos from Google maps). Left: In the Background: whole Germany and parts of Europe. In the zoomed part (red rectangle): the scanned Mangfall area (marked in green) from the Tegernsee in the south to the highway in the north. Top right: clip from the Tegernsee of the scanned area. Bottom right: scanned data with the point's intensity as grey value.

5 Discussion

This paper has summarized currently existing methods for point cloud processing. This paper gives a short overview of existing methods for point cloud processing. A more detailed overview can be found in WEINMANN (2016). These methods include full waveform analysis, classification, registration and change detection tasks. In the special task of river surveying, bathymetric applications and some laser scanner devices are also proposed. Since the European directive 2007/60/ EC demands the creation of change maps, the change detection task with bathymetric data becomes more important. Currently used methods for point cloud classification and registration mostly use a point wise algorithm. Such a point wise processing can become unnecessary computational expensive with very big point clouds (up to 200 Mio points). Therefore, a voxel structure should be used to generalize such big point clouds in a better way. A very difficult task is the registration in non-urban areas. There exist no rigid structures or shapes which can be used for the registration task. Furthermore, also the registration should be handled with a voxel structure to get big point cloud processable.

In this context, the paper introduced the idea of defining a voxel structure and use this structure for all processing tasks. In future work, the authors will introduce these voxel structure and approaches for classification, registration and change detection on the base of voxels. The special interest will be the change detection of topobathymetric point clouds. The classification must be able to differentiate between dry and wet ground points.
The first task of point cloud classification is currently under construction but the authors reaches first good results for the segmentation task. Fig. 3 show the first result of a voxel based ground detection.

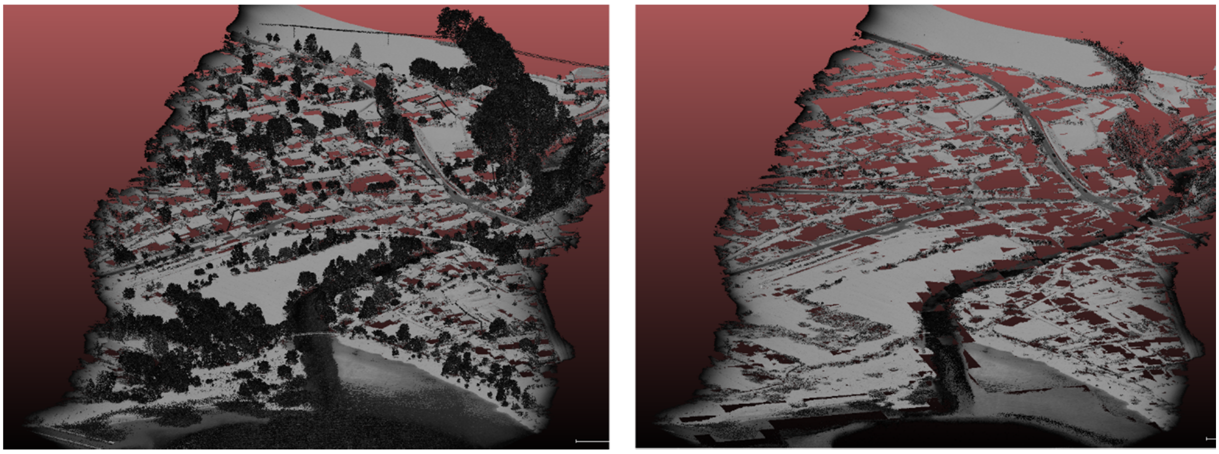

Fig. 3: Result of a voxel based ground detection. Left: original data with intensity as grey value. Right: ground points with intensity as grey value.

These ground segments are handled as the first class and the non-ground points will be segmented and matched to the other classes in the future. The voxel based ground detection will be introduced in a future paper when the parameter adjustment is done correctly. This ground detection is a fast version, which processes the shown 5 Mio points in Fig. 3, in less than 1 second on a single thread and is highly parallelizable. For the processing an intel core i7-6820HQ CPU with 2.7 GHz was used. In short, the used method is to use the position of voxels to detect the lowest ones in a local area. Because of the footprints of roofs, roof points which are marked as ground need to be filtered. The used filter looks for big distances of the height coordinate of neighboured voxels. Since steep slopes create big distances in height too, they are marked as non-ground points as well as roof points (this is called overcut). If there is noise between the roof and the ground, or the building is very flat, some roof points are still marked as ground points (this is called undercut). The undercut and overcut are shown in Fig. 4 on the example of a part of Gmund (a Village north to the Tegernsee, which can be seen in Fig. 3).

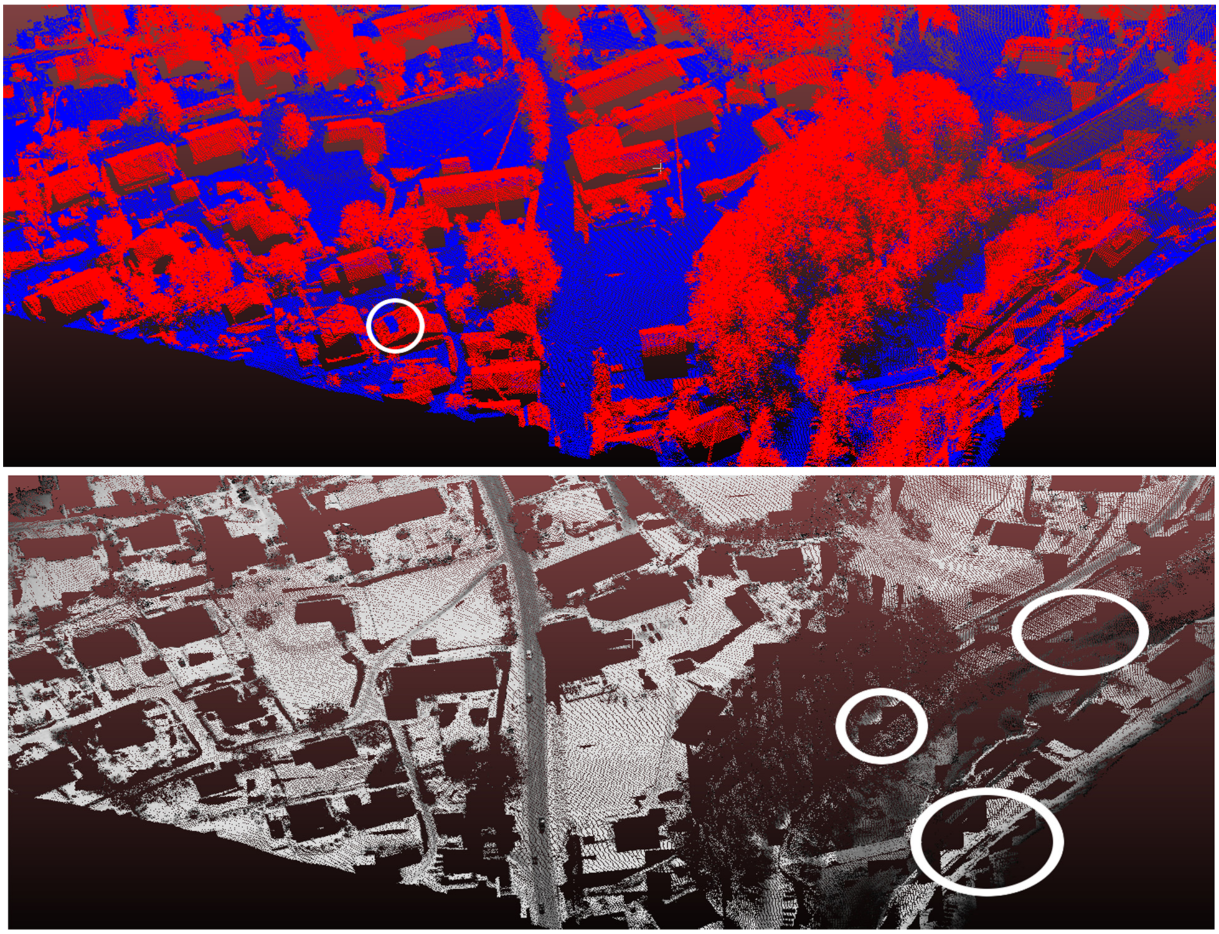

Fig. 4: Some problems with the ground detection. Top: coloured point types blue = ground, red = others. Marked area: undercut, some roof points detected as ground. Bottom: ground points with intensity as grey value. Marked areas: overcut, some points of steep slopes are not marked as ground points.

Future work will pursue the idea to create a filter for wrong classifications by looking at the neighbourhood. An undercut like in Fig. 4 will result in a small ground area inside a roof area. Therefore, the ground area should be marked as roof area. The same filter should be able to decimate the overcuts. This are areas of another class inside a ground area and therefore marked as ground.

In summary, the special interest of future work will be the introduction of methods for automatic point cloud classification, registration and change detection, which can handle big point clouds in a suitable time. Therefore, these methods will fully depend on a voxel structure to make the processing time independent of the point cloud's number of points. These methods should also be able to process non-urban and non-rigid areas.

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